Circular Traffic Signs Recognition Using The Number of Peaks Algorithm

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Abstract

Smart cars nowadays include embedded computers to guide the driver in his trip. An important application that should be added to any car is the detection and recognition of traffic signs. In this paper, we focus on the recognition of a wide set of circular traffic signs using the Number of Peaks Algorithm [1]. After detecting a traffic sign, the algorithm draws three horizontal lines and three vertical lines across the image. The number of peaks (crossing from a black pixel to a white pixel) is calculated for each of the six lines as the image is scanned from right to left (for horizontal lines) or top to bottom (for vertical lines). The resulting numbers of peaks are used by the decision-tree-like search algorithm to distinguish between 51 circular road signs with a mean detection time of 8 milliseconds, 100% detection rate and in a fairly noisy environment.

Keywords: Traffic Signs Recognition, Pattern Recognition, Image Processing, Autonomous Cars.

1. INTRODUCTION

Automatic detection and recognition of traffic signs is an important addition to any smart car. Having such a tool in a car would alert the driver to possible obstacles or changes in the road and therefore reduce the possibility of accidents. Previous systems for real time detection of traffic signs are limited to a small set of circular or triangular signs [2, 3]. A system capable of recognizing all traffic signs within an acceptable amount of time for a moving car is highly desirable.

In this paper, a system is described that recognizes a wide set of circular traffic signs. The system uses a novel algorithm, the number of peaks algorithm, to differentiate between 51 circular road signs in a fast and reliable manner. Many researchers studied the detection and recognition of traffic signs since 1996 [1-21]. Most of the approaches to traffic sign recognition follow a two-step algorithm. The first step is the detection of a traffic sign in the image and the second step is to recognize the sign. The second step may involve classification of the sign first into predefined classes, such as triangular signs or speed signs, followed by recognition of a specific sign [4, 5, 6]. In the recognition phase, various approaches are available in the literature [7]. Most approaches are pixel-based using cross-correlation template matching [4, 8] or neural networks [5]. However, other approaches exist that are feature-based. For example, in [9] statistical properties, such as moments found from the binary images of the central part of sign candidates, were used. Local edge orientations and density at arbitrary fixation points were used [10].

A different approach was also presented in [6, 7] based on the similarities of the detected sign and the sign images stored in the template. Equiangular polygons are detected in a filtered image then a discrete-color image of this object is compared with model images. Another technique [11] uses error correcting output codes (ECOC) to build a system for multi-class classification of traffic signs. In all cases classification methods consider a limited number of signs such as six circular signs [2] or blue traffic signs [3] and are characterized by varying recognition rate 81% [3], 76% to 91% [7], and 98.66% [11].

Section 2 introduces the number of peaks algorithm. Section 3 introduces the decision trees used in the algorithm and details how a specific sign is distinguished based on number of peaks in horizontal and vertical lines. Section 4 discusses the performance of the algorithm. Section 5 concludes the paper and gives suggestions for future research.

2. THE NUMBER OF PEAKS ALGORITHM

The number of peaks algorithm works after a traffic sign is detected. Figure 1 shows all possible images of circular signs recognized by the Number of Peaks Algorithm. Figure 1 shows each sign along with a number assigned to it. This number is used in the flowcharts of the algorithm to distinguish between the signs as shown in the next section.

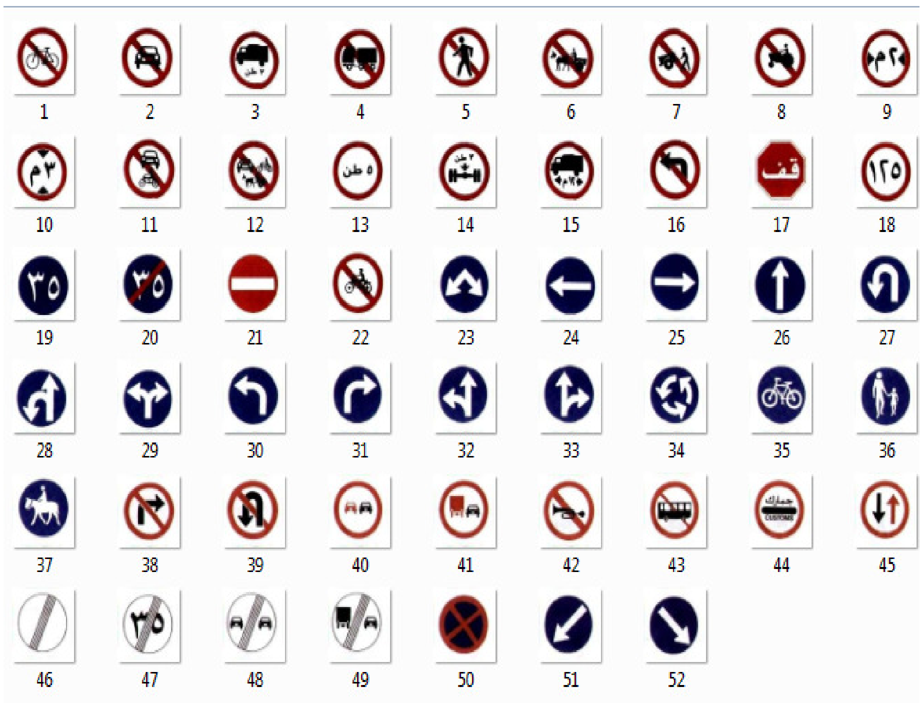

FIGURE 1: Circular Traffic signs recognized by the Number of Peaks Algorithm and their number representation.

Once a traffic sign is detected, its negative image representation is generated as shown in Figure 2.

FIGURE 2: A sign and its negative image representation.

Then a factor f is selected from a discrete set {1/3, 1/4, 1/5, 1/9, 1/10}. This factor is used to select the positions of three horizontal lines and three vertical lines to be drawn across the image. Lines T, H and B (in Figure 3) are horizontal lines. Line T is at a distance f of the total image length taken from the image top. Line H is drawn at the middle of the image horizontally. Line B is drawn at a distance f of the total image length taken from the image bottom. Similarly, lines R, V and L are three vertical lines drawn across the image at distances f of the total width from the image right boundary, at the middle and f of the total width from the image left boundary respectively.

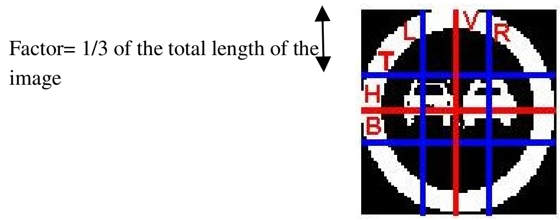

FIGURE 3: Crossing lines of an Image.

F=1/3	H	T	B	V	L	R	
26	2	3	2	2	1	1	
50	1	1	1	1	1	1	
21	2	1	1	2	2	2	
24	2	1	2	2	2	2	
25	2	1	2	2	2	4	
28	2	2	5	2	2	2	
30	2	2	2	2	2	2	
31	2	3	2	2	2	2	
23	3	2	3	2	2	3	
32	3	2	3	3	2	2	R 1/5 (1)
33	3	2	3	3	2	2	R 1/5 (2)
27	3	3	3	2	2	2	
51	3	3	2	3	2	2	
29	4	3	2	2	2	4	
37	4	3	5	4	2	2	
18	6	4	4	3	2	4	
20	4	4	2	2	3	3	
10	4	5	3	3	3	4	
16	5	3	3	3	3	3	
19	4	4	3	2	3	3	
4	4	4	4	3	3	4	
5	4	4	4	4	3	4	
39	3	4	4	5	3	3	
45	4	4	4	3	3	3	
35	10	4	5	5	3	6	
13	6	2	2	4	4	2	
6	5	4	7	4	4	3	
8	3	4	5	4	4	3	
34	3	3	4	3	4	3	
9	4	3	3	2	4	4	
42	4	3	3	4	4	4	
7	5	4	5	3	4	4	
2	5	3	4	4	4	4	R 1/5 (2)
38	5	3	4	4	4	4	R 1/5 (3)
17	6	4	3	5	4	4	
36	6	3	5	2	4	4	
41	4	3	2	3	4	5	
40	6	2	2	2	5	5	
1	7	4	5	4	5	6	
3	3	4	5	4	5	4	
43	4	3	5	4	5	4	
14	5	3	6	5	5	4	
15	2	4	6	4	5	4	
46	7	5	7	7	5	5	
47	8	4	7	6	5	7	
11	4	4	3	6	6	4	
12	8	4	4	5	6	4	
22	4	4	5	4	6	3	
44	3	9	5	6	6	5	
48	8	5	7	7	6	6	
49	9	7	5	7	7	6	

TABLE 1: Grouping of the Signs by the number of Peaks of the L line.

A Peak is defined as a crossing from a black pixel to a white pixel [1, 22] as the image is scanned from right to left (for lines T, H and B) or top to bottom (for lines R, V and L). A line starting with white pixels is considered to have one peak at the beginning. Line T in Figure 3 contains two sections where there is a transition from black pixels to white pixels. This means that for the line labeled H, the algorithm would return a value of 2.

3. DECISION TREES FOR THE NUMBER OF PEAKS ALGORITHM

The number of peaks for all 6 lines using factors 1/3 and 1/5 were calculated for all the circular traffic signs considered (51 in total). Those numbers were studied to find out the minimum number of lines that can be used to recognize each image. For all the images, we started out with the line that would divide those images into the maximum number of groups. Then use another line to keep dividing the groups until recognizing all the images. The results are summarized in Table 1. Table 1 is sorted according to the lines that were used to identify the signs. Given a circular traffic sign to be recognized, the algorithm starts with a factor of 1/3. The number of peaks for the L line is found. This number divides all the circular traffic signs into seven groups as shown in Table 1. If this number is 1, then the studied sign is either number 26 or number 50. The number of peaks for the V line is then found. If this value is 2 then the sign is number 26. If this value is 1, then the sign is number 50.

These results can also be seen in the flowchart shown in Figure 4. If the number of peaks for the L line is 3, then the candidate sign is a sign belonging to the set {20, 10, 16, 19, 4, 5, 39, 45, 35}. The number of peaks for additional lines should be found (B then T then R then V) to identify those signs. The remaining parts of the flowchart for the nodes labeled H, R1 and B2 are continued in Figures 5, 6 and 7 because of space limitation.

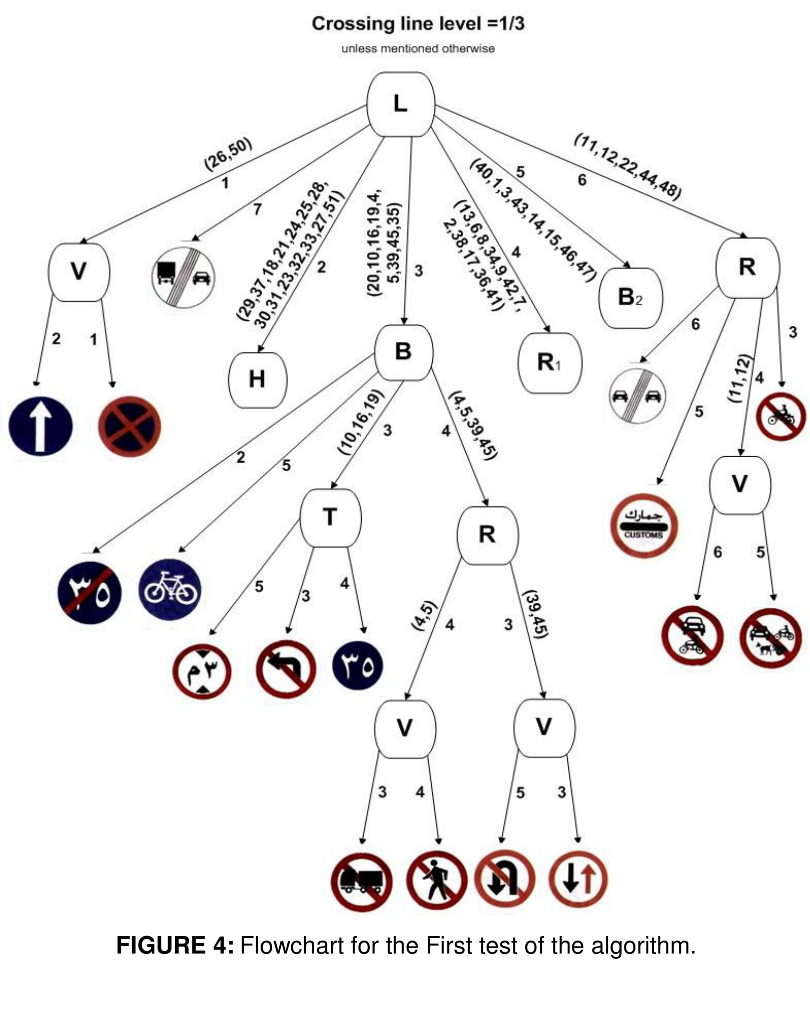

FIGURE 4: Flowchart for the First test of the algorithm.

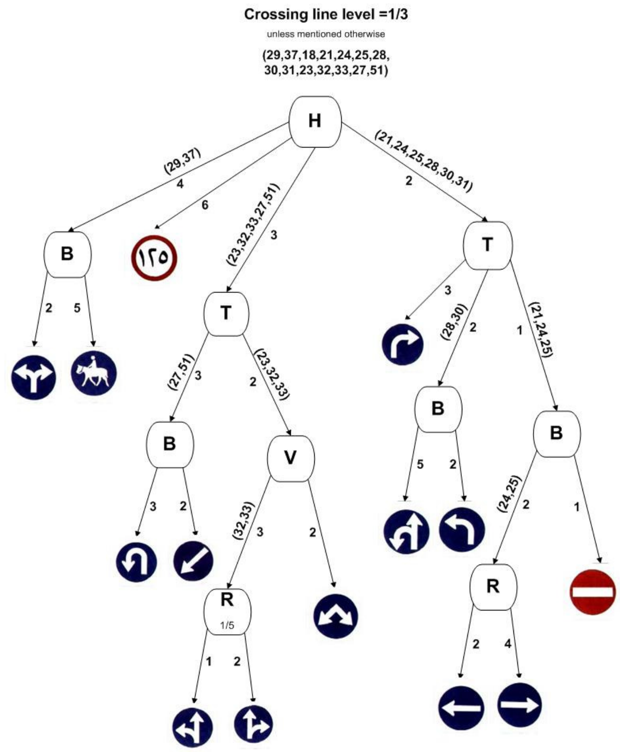

FIGURE 5: Flowchart for node H of Figure 4.

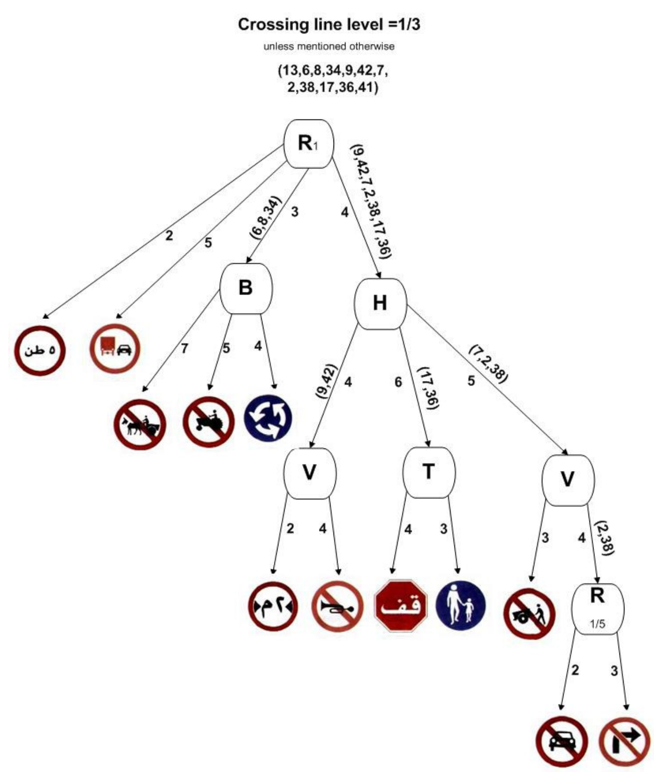

FIGURE 6: Flowchart for node R1 of Figure 4.

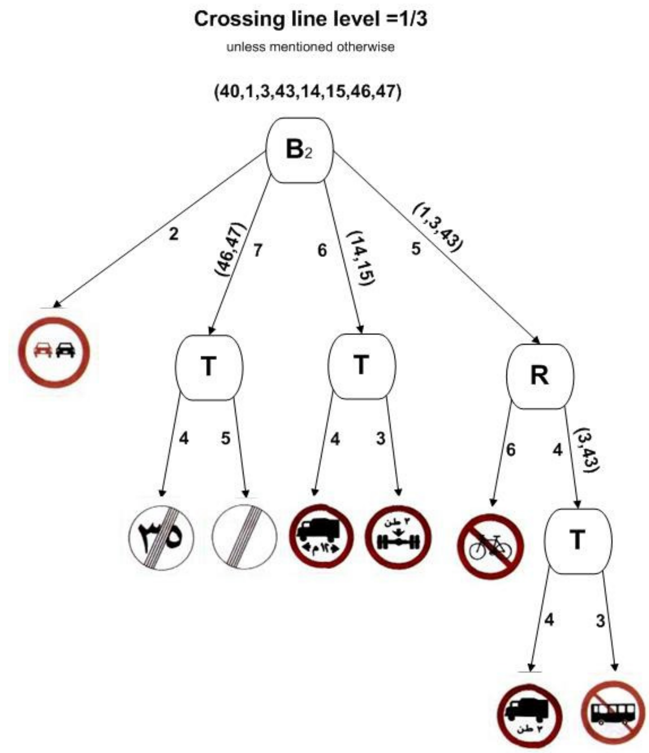

FIGURE 7: Flowchart for node B2 of Figure 4.

4. RESULTS

The algorithm was repeated 1000 times to recognize each of the 51 signs on an HP 8200 Elite with an I5 2500 CPU at 3.30 GHz. The average detection time for a sign is 8 milliseconds.

In order to test the performance of the Number of Peaks Algorithm in blurred images, noise was artificially introduced to the signs considered and the algorithm was run on the resulting noisy images. Artificially introduced errors were simulated using equation (1)

$$P = Q + \mu N \qquad (1)$$

Where matrix Q is representing the image, and N is of a same size as Q, which consists of uniformly distributed pseudo-random numbers and μ is a constant, which is used to control the amount of noise to introduce in the image. Performance is measured using the Frobenius norm of (P - Q). The Frobenius norm of an m × n matrix A is defined by the following equation (2).

$$\|A\|_F = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} |a_{ij}|^2} \qquad (2)$$

A graph of the mentioned norm as a function of μ is shown in Figure 8. We can see that the solid line shows the averaged calculated threshold over the range of values of μ for different type of circular signs where the noisy image can be recognized by the algorithm, and the dashed line shows the averaged threshold for the value of μ where the character would not be recognized by the Human eye. The human eye threshold was determined based on our responses to the given noisy images. It turns out that the value of the threshold of recognition is equal to μ = 1.08, with an equivalent human eye threshold of 1.7. This means that our system would be able to work within a fairly noisy environment even when the amount of noise changes the features important to the algorithm drastically. However the system is still inferior to a human being in the same environment.

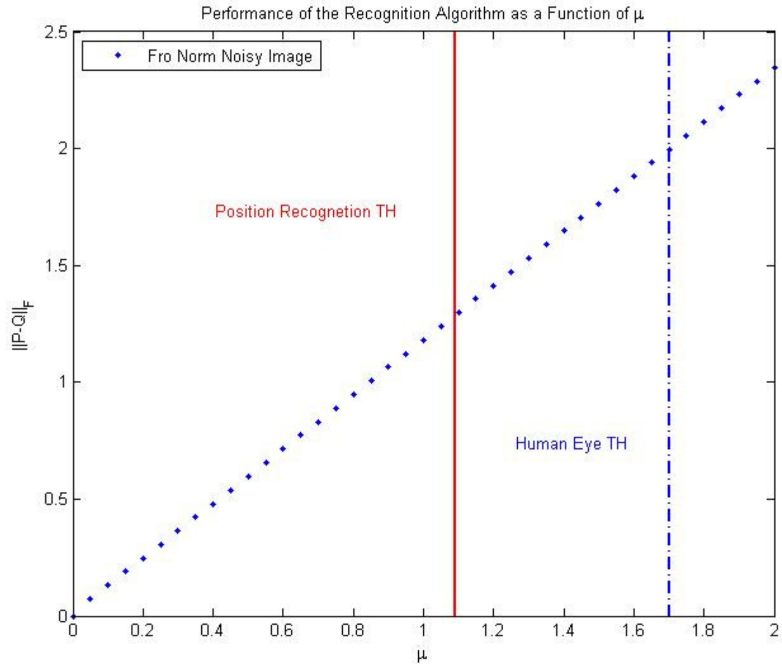

FIGURE 8: Performance of the Frobenius norm.

Even in artificially induced noisy images, the detection rate of the Number of Peaks algorithm is 100% up to some level of noise added.

FIGURE 9: A sign with added noise having μ=1.08.

Figure 9 shows in the top row an image used in this simulation and its negative generated image. In the second row, the noisy image having a μ=1.08 is shown and the corresponding negative image that was successfully recognized by the number of peaks algorithm.

5. CONCLUSION AND FUTURE RESEARCH

In this paper an algorithm for recognition of 51 circular road signs was presented. The algorithm uses a simple method that requires a minimum number of image processing combined with a decision-tree-like search algorithm. The algorithm was repeated 1000 times to recognize each of the 52 signs on an HP 8200 Elite with an I5 2500 CPU at 3.30 GHz. The average detection time for a sign ranged between 8 milliseconds for sign number 11 to 9.5 milliseconds for sign number 23, with an average detection time of 8.47 milliseconds. Even in artificially induced noisy images, the detection rate of the Number of Peaks algorithm is 100% up to some value of the noise parameter μ.

The next step of this research is to extend this sign recognition algorithm to recognize signs of any shape using the same principle. Flowcharts similar to the ones presented in Figures 4 to 7 should be drawn to detect all traffic signs. The system should then be integrated into a full real time system to detect and then recognize all classes of traffic signs in any country. Shape recognition can be investigated to help detect and locate the sign in real time images. The algorithm should be implemented on portable hardware and installed in smart cars. Since the time to detect and recognize a sign should be minimized for the system to be useful in high speed zones, a parallel version of this algorithm should be created and tested on multicore processors and compared to the performance of implementing this algorithm on Field Programmable Gate Arrays (FPGA).

6. ACKNOWLEDGMENT

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